A REVIEW ON CONTENT BASED IMAGE RETRIEVAL

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ABSTRACT

In current years, very huge collections of images and videos have grown swiftly. In parallel with this boom, content-based image retrieval and querying the indexed collections of images from the large database are required to access visible facts and visual information. Three of the principle additives of the visual images are texture, shape and color. Content based image retrieval from big sources has a wide scope in many application areas and software's. To accelerate retrieval and similarity computation, the database images are analyzed and the extracted regions are clustered or grouped together with their characteristic feature vectors. As a result of latest improvements in digital storage technology, it's easy and possible to create and store the large quantity of images inside the image database. These collections may additionally comprise thousands and thousands of images and terabytes of visual information like their shape, texture and color. For users to make the most from those image databases, efficient techniques and mechanisms of searching should be devised. Having a computer to do the indexing primarily based on a CBIR scheme attempts to deal with the shortcomings of human-based indexing. Since anautomated process on a computer can analyze and process the images at a very quick and efficient rate that human can never do alone. In this paper, we will discuss the structure of CBIR with their feature vectors.

Keywords

Content based image retrieval (CBIR), color histogram, color, shape, texture features.

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INTRODUCTION

With the advancement in internet and multimedia technologies, a huge amount of multimedia data in the form of audio, video and images has been used in many fields like medical treatment, satellite data, video and still images repositories, digital forensics and surveillance system. This has created an ongoing demand of systems that can store and retrieve multimedia data in an effective way. Many multimedia information storage and retrieval systems have been developed till now for catering these demands. The most common retrieval systems are Text Based Image.

Retrieval (TBIR) systems, where the search is based on automatic or manual annotation of images. A conventional TBIR searches the database for the similar text surrounding the image as given in the query string. The commonly used TBIR system is Google Images. The text based systems are fast as the string matching is computationally less time consuming process. However, it is sometimes difficult to express the whole visual content of images in words and TBIR may end up in producing irrelevant results. In addition, annotation of images is not always correct and consumes a lot of time. For finding the alternative way of searching and overcoming the limitations imposed by TBIR systems more intuitive and user friendly content based image retrieval systems (CBIR) were developed. A CBIR system uses visual contents of the images described in the form of low level features like color, texture, shape and spatial locations to represent the images in the databases. The system retrieves similar images when an example image or sketch is presented as input to the system. Querying in this way eliminates the need of describing the visual content of images in words and is close to human perception of visual data. Due to exponential increase of the size of the so-called multimedia files in recent years because of the substantial increase of affordable memory storage on one hand and the wide spread of the World Wide Web (www) on the other hand, the need for efficient tool to retrieve images from large dataset becomes crucial. This motivates the extensive research into image retrieval systems [1]. From historical perspective, one shall notice that the earlier image retrieval systems are rather text -based search since the images are required to be annotated and indexed accordingly. However, with the substantial increase of the size of images as well as the size of image database, the task of user -based annotation becomes very cumbersome, and, at some extent, subjective and, thereby, incomplete as the text often fails to convey the rich structure of the images. This motivates the research into what is referred to as content-based image retrieval (CBIR).

Content-based image retrieval (CBIR) has become an important research area in computer vision as digital image collections are rapidly being created and made available to multitudes of users through the World Wide Web. There are collections of images from art museums, medical institutes, and environmental agencies, to name a few. In the commercial sector, companies have been formed that are making large collections of photographic images of real-world scenes available to users who want them for illustrations in books, articles, advertisements, and other media meant for the public at large. The largest of these companies have collections of over a million digital images that are constantly growing bigger. Incredibly, the indexing of these images is all being done manually–a human indexer selects and inputs a set of keywords for each image [2]. Each keyword can be augmented by terms from a thesaurus that supplies synonyms and other terms that previous users have tried in searches that led to related images. Keywords can also be obtained from captions, but these are less reliable.Content-based image retrieval research has produced a number of search engines. The commercial image providers, for the most part, are not using these techniques. The main reason is that most CBIR systems require an example image and then retrieve similar images from their databases. Real users do not have example images; they start with an idea, not an image. Some CBIR systems allows users to draw the sketch of the images wanted [3]. Such systems require the users to have their objectives in mind first and therefore can only be applied in some specific domains, like trademark matching, and painting purchasing. Earlier CBIR systems rely on global image features, such as color histogram and texture statistics. Global features cannot capture object properties, so local features are favored for object class recognition. For the same reason, higher-level image features are preferred to lower-level ones. Similar image elements, like pixels, patches, and lines can be grouped together to form higher-level units, which are more likely to correspond to objects or object parts. Different types of features can be combined to improve the feature discriminability. For example, using color and texture to identify trees is more reliable than using color or texture alone [4]. The context information is also helpful for detecting objects. A boat candidate region more likely corresponds to a boat if it is inside a blue region. While improving the ability of our system by designing higher-level image features and combining individual ones, we should be prepared to apply more and more features since a limited number of features cannot satisfying the requirement of recognizing many different objects in ordinary photographic images. To open our system to new features and to smooth the procedure of combining different features, we propose a new concept called an abstract region; each feature type that can be extracted from an image is represented by a region in the image plus a feature vector acting as a representative for that region. The idea is that all features will be regions, each with its own set of attributes, but with a common representation. This uniform representation enables our system to handle multiple different feature types and to be extendable to new features at any time.

In a typical CBIR system (Figure 1), image low level features like color, texture, shape and spatial locations are represented in the form of a multidimensional feature vector. The feature vectors of images in the database form a feature database. The retrieval process is initiated when a user query the system using an example image or sketch of the object. The query image is converted into the internal representation of feature vector using the same feature extraction routine that was used for building the feature database. The similarity measure is employed to calculate the distance between the feature vectors of query image and those of the target images in the feature database. Finally, the retrieval is performed using an indexing scheme which facilitates the efficient searching of the image database. Recently, user's relevance feedback is also, incorporated to further improve the retrieval process in order to produce perceptually and semantically more meaningful retrieval results. In this chapter, we discuss these fundamental techniques for content- based image retrieval. CBIR is the application of computer vision to aid the image retrieval process of searching for digital images in large database based on the comparison of low level features of images. The search is carried out by using contents of the image themselves rather than relying on human-inputted metadata such as caption or keyword describing the image. Compared to text-based retrieval systems, CBIR is more feasible in large-scale databases and is usually used in environments which require fast retrieval and real-time operations. Software's which implements CBIR are known as content-based image retrieval systems (CBIRS). CBIR came to the interest of researchers as it offers the ability to index images based on content of the image itself [4]. CBIR retrieves images based on visual features such as colour, texture and shape [2]. In this method, color, shape and texture of an image are classified automatically or semi-automatically with the aid of human classifier. Retrieval results are obtained by calculating the similarity between the query and images stored in the database using predefined distance measure. The results are than ranked according to the highest similarity score.

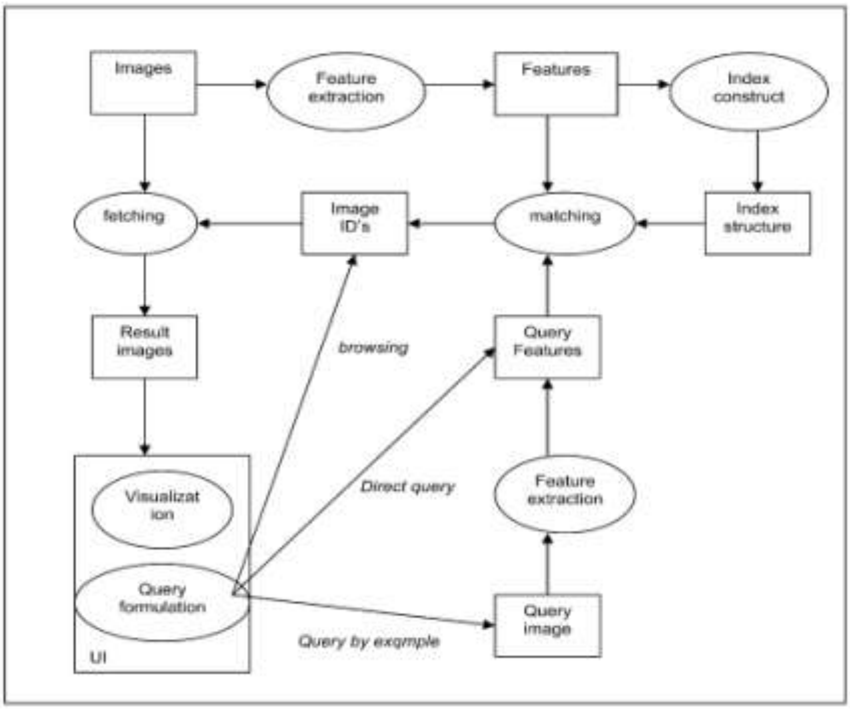

Figure 1. CBIR Architecture

TEXT-BASED RETRIEVAL AND CONTENT-BASED RETRIEVAL

An image retrieval system is a computer system for browsing, searching and retrieving images in an image database. Text-based and content-based are the two techniques adopted for search and retrieval in image database. In text-based retrieval, images are indexed using keywords, subject headings or classification codes, which in turn are used as retrieval keys during search and retrieval. Text-based retrieval is non-standardized because different users use different keywords for annotation [7]. Text descriptions are sometimes subjective and incomplete because it cannot depict complicated image features very well. Examples are texture images that cannot be described by text. In text retrieval, humans are required to personally describe every image in the database, so for a large image database the technique is cumbersome, expensive and labor-intensive. Content-based image retrieval (CBIR) technique use image content to search and retrieve digital images.

Content-based image retrieval system was introduced to address the problems associated with text-based image retrieval, (H. Jegou, 2010). Advantages of content-based image retrieval over text-based retrieval will be mentioned in the next sections. However, text-based and content-based image retrieval techniques complement each other. Text-based techniques can capture high-level feature representation and concepts. It is easy to issue text queries but text based techniques cannot accept pictorial queries. On the other hand, content-based techniques can capture low-level image features and accept pictorial queries. But they cannot capture high-level concepts effectively. Retrieval systems exist which combine both techniques for more efficient retrieval.

COLOUR FEATURES

Color is one of the major features used in CBIR systems. This popularity is attributed to the ease in implementation and the distinguishing differences between colors. It is a robust feature to changes such as the scene layout or viewing angle. Color can be represented with different models such as HSI, YIQ, CMY and RGB.The RGB model is the most widely known one and can be visualized as a cube. One corner of the cube is the origin L (0, 0, and 0) and each of the three primary colors Red, Green and Blue are assigned an edge to represent the axis from the origin. Any other individual color obtained after combining the red, green and blue components in certain proportions then lie in this coordinate space. The origin represents black as it is the point of lowest red, green and blue values. Understandably, the opposite corner with the highest red, green and blue values represents white. The 3D coordinate space is similar to the way our three sets of retinal cones work in our human visual system [7]. The RGB model is nonetheless limited in representing the full human perception which includes details such as the brightness and purity of a color. Those are however implicit in the coordinate space and the nonlinear transformation from RGB to HSI is used to capture those additional properties.

Comparing the color content of images is an obvious, and consequently popular, choice for performing image retrieval duties. Color acts as a robust descriptor that can often simplify the tasks of object identification and extraction from a given image [8]. For example, in Figure 2it is much easier to locate image pixels of the flower from the rest of the image when using the color image as opposed to the grayscale version. Due to the very nature of color representation, the color data itself provides multiple measurements at any given pixel location in an image. Because of the inherent properties of color, the last two decades have produced a number of interesting methods by which color image retrieval can be performed. A selection of these methods will be discussed following a review of the fundamentals of color and its methods of representation.

Figure 2. A color and grayscale version of an image illustrating the advantages of color

TEXTURE-BASED CBIR

Another famous method to CBIR entails the use of texture in order to index database photos. Texture inside the realm of photograph processing gives data approximately the nearby spatial arrangement of colors or intensities in a given photograph [10]. Images that have similar texture houses need to therefore have the same spatial arrangements of colors or intensities, but not necessarily the equal colors. Because of this, the use texture-based image indexing and retrieval techniques is quite unique than those used strictly for color. In the field of laptop imaginative and prescient and photograph processing, there is no uncomplicated definition of texture. This is because to be had texture definitions are based totally on texture evaluation methods and the capabilities extracted from the photograph. However, texture can be concept of as repeated styles of pixels over a spatial area, of which the addition of noise to the styles and their repetition frequencies results in textures which can appear like random and unstructured [9]. Texture houses are the visible patterns in a photo that have properties of homogeneity that do not result from the presence of most effective a single color orIntensity. The unique texture homes as perceived by means of the human eye are, as an instance, regularity, directionality, smoothness, and coarseness, see Figure 3.

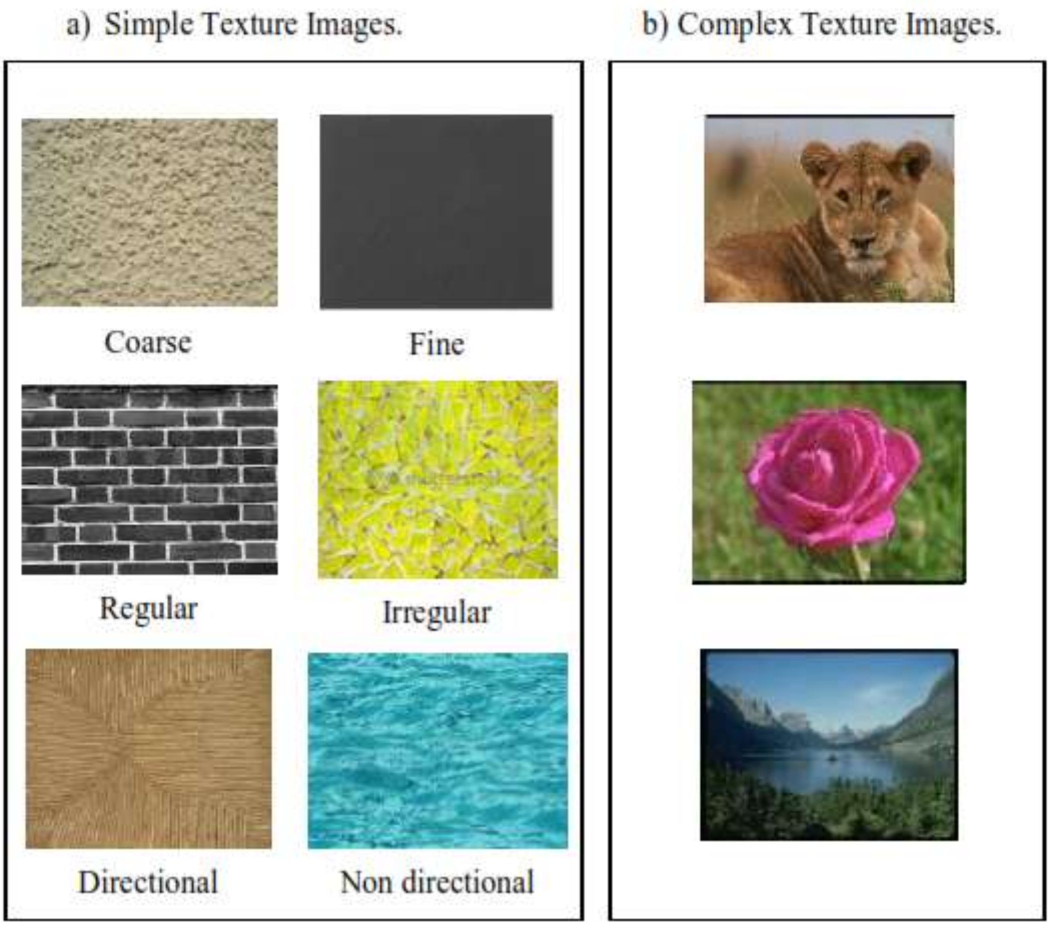

Figure 3. Examples of simple and complex texture images

SHAPE FEATURES

Shape feature provides the most important semantic information about an image. Shape features are usually described using part or region of an image. The accuracy of shape features largely depends upon the segmentation scheme used to divide an image into meaningful objects [13]. However, fast and robust segmentation is difficult to achieve. This limits the shape features only to those retrieval applications where objects or region of images are readily available. The shape descriptors are categorized into two classes: boundary based descriptor and region based descriptor. Some boundary based representative shape description techniques are chain codes, polygonal approximations, Fourier descriptor and finite element model [15]. On the other hand state of the art region based descriptors are statistical moment and area. A good shape feature should be invariant to translation, rotation and scaling.

SPATIAL INFORMATION

The performance of an image retrieval system can be improved by considering spatial locations of different objects in the image. The spatial location of objects and their relationship can provide useful discriminating information in image retrieval applications [15]. For instance, parts of blue sky and ocean may have similar color histograms, but their spatial locations in images are different. The spatial location matching can be implemented by matching the images based on fixed location similarity. In this approach a similar object lying in different regions of an image cannot be detected [16]. For instance; image having tiger in the left part may not get similarity with images having tiger in the right part of images. To overcome this problem systems compare all region of image with the query object or region. This may result in the increase of response timeof the system. The most commonly used techniques for finding spatial location similarity includes 2D strings, spatial quad-tree and symbolic images.

SIMILARITY MEASURE

The degree of similarity between query and target images is calculated based on the value of similarity measure. The images are ranked according to their similarity value and presented as output of CBIR system. Often, the choice of similarity measure affects the performance of retrieval system. Many similarity measures have been developed over the years based on the quantitative estimates of the distribution of features in the image. Some of the most commonly used similarity measures employed in CBIR are Euclidean distance , Minkowski- form distance, Histogram intersection distance, Quadratic- form distance, Mahalanobis distance and KullbackLeibler (KL) divergence distance.

APPLICATIONS

A wide range of possible applications for CBIR technology has been identified. Potentially fruitful areas include:

•Crime prevention

•The military

•Intellectual property Architectural and engineering design

•Fashion and interior design

•Journalism and advertising

•Medical diagnosis

•Geographical information and remote sensing systems

•Cultural heritage

•Education and training

•Home entertainment

•Web searching.

RELATED WORK

Savvas A. Chatzichristofis et al. (2008) deals with a new low level feature that is extracted from the images and can be used for indexing and retrieval. This feature is called “Color and Edge Directivity Descriptor” and incorporates color and texture in formation in a histogram. CEDD size is limited to 54 bytes per image, rendering this descriptor suitable for use in large image databases.

Chuen-Horng Lin et al. (2008) proposes three feature vectors for image retrieval. In addition, a feature selection technique is also brought forward to select optimal features to not only maximize the detection rate but also simplify the computation of image retrieval. The first and second image features are based on color and texture features, respectively called color co-occurrence matrix (CCM) and difference between pixels of scan pattern (DBPSP) in this research work. The third image feature is based on color distribution, called color histogram for K-mean (CHKM). CCM is the conventional pattern co-occurrence matrix that calculates the probability of the occurrence of same pixel color between each pixel and its adjacent ones in each image, and this probability is considered as the attribute of the image.

Michal Perdoch et al. (2009) proposes a novel method for learning discretized local geometry representation based on minimization of average reprojection error in the space of ellipses. The representation requires only 24 bits per feature without drop in performance. Additionally, they showed that if the gravity vector assumption is used consistently from the feature description to spatial verification, it improves retrieval performance and decreases the memory footprint.

HerveJegou et al. (2010) addresses the problem of image search on a very large scale, where three constraints have to be considered jointly the accuracy of the search, its efficiency, and the memory usage of the representation. They first proposed a simple yet efficient way of aggregating local image descriptors into a vector of limited dimension, which can be viewed as a simplification of the Fisher kernel representation. They then showed how to jointly optimize the dimension reduction and the indexing algorithm, so that it best preserves the quality of vector comparison.

SwapnaliniPattanaik et al. (2012) gives an overview idea of retrieving images from a large database. CBIR is used for automatic indexing and retrieval of images depending upon contents of images known as features. The features may be low level or High level. The low-level features include color, texture and shape. The high-level feature describes the concept of human brain. The difference between low level features extracted from images and the high-level information need of the user known as semantic gap.

Yanzhi Chen et al. (2012) proposed a discriminative criterion for improving result quality. This criterion lends itself to the addition of extra query data, and they showed that multiple query images can be comb index to produce enhanced results. Experiments compare the performance of the method to state-of-the-art in object retrieval, and show how performance is lifted by the inclusion of further query images.

ReljaArandjelovi´c et al. (2012) made the following three contributions: (i) a new method to compare SIFT descriptors (RootSIFT) which yields superior performance without increasing processing or storage requirements; (ii) a novel method for query expansion where a richer model for the query is learnt discriminatively in a form suited to immediate retrieval through efficient use of the inverted index; (iii) an improvement of the image augmentation method proposed by Turcot and Lowe where only the augmenting features which are spatially consistent with the augmented image are kept.

Sumaira Muhammad et al. (2012) has given comparison of three different approaches of CBIR based on image features and similarity measures taken for finding the similarity between two images. Results have shown that selecting an important image feature and calculating that through a meaningful way is of great importance in image retrieval. All the important features must be considered while constructing a feature vector and a proper similarity measure should be used for calculating the distance between two feature vectors.

GhanshyamRaghuwanshi et al. (2015) proposes a novel technique for texture image retrieval based on tetrolate transforms. Tetrolates provide fine texture information due to its different way of analysis. Tetraamines are applied at each decomposition level of an image and best combination of tetraamines is selected, which better shows the geometry of an image at each level. All three high pass components of the decomposed image at each level are used as input values for feature extraction.

Jitendra Singh et al. (2016) proposes the content based image retrieval as one of most technique of data and multimedia technology. As image collections are growing at a rapid rate, and demand for efficient and effective tools for retrieval of query images from database is increased significantly. Between, content-based image retrieval systems have become very popular for browsing, in searching and retrieving images from a large database of digital images as it requires relatively less human intervention.

Zhijie Zhao et al. (2016) proposes a scheme which is based on three noticeable algorithms: color distribution entropy(CDE), color level co-occurrence(CLCM) and invariant moments. CDE takes the correlation of the color spatial distribution in an image into consideration. CLCM matrix is the texture feature of the image, which is a new proposed descriptor that is grounded on co-occurrence matrix to seize the alteration of the texture.

RESEARCH MOTIVATION

Image retrieval is an extension to traditional information retrieval. Approaches to image retrieval are somehow derived from conventional information retrieval and are designed to manage the more versatile and enormous amount of visual data which exist. Low-level visual features such as color, texture, shape and spatial relationships are directly related to perceptual aspects of image content. Since it is usually easy to extract and represent these features and fairly convenient to design similarity measures by using the statistical properties of these features, a variety of content-based image retrieval techniques have been proposed in the past few years. High-level concepts, however, are not extracted directly from visual contents, but they represent the relatively more important meanings of objects and scenes in the images that are perceived by human beings. These conceptual aspects are more closely related to users’ preferences and subjectivity. Concepts may vary significantly in different circumstances. Subtle changes in the semantics may lead to dramatic conceptual differences. Needless to say, it is a very challenging task to extract and manage meaningful semantics and to make use of them to achieve more intelligent and user friendly retrieval.

• The semantic gap between the user's needs and the capability of CBIR algorithms remains significant. Significant effort has been put into using low-level image properties such as color.

•As number of images present in the database may be in large quantity, it takes a lot of time to decompose each and every image from the database using Haar wavelet transformation.

•The existing system is providing an interactive mechanism that allows the user to provide the feedback of the retrieved image will be very hectic. It is not possible for the user to interact with the system for large number of retrieved images.

•The empty spaces are created in original image by using preprocessing and transformations leads to destroy the actual quality of image.

•User does not get the consistent result of the choice in existing CBIR algorithms and complexity of the system increases and it will involve extra hardware and thereby increasing the cost.

FEATURE EXTRACTION FROM IMAGES

The extraction of the texture and color content of the images take place bothduring the database population phase and querying phase. Depending on theuser’s intention, the texture feature extraction can be performed in three diff erent
ways:

Fully Automatic Texture Feature Extraction: The system is capableof determining a rectangular region on the image representing the texturecharacteristics of the image. Since this region is relatively smaller than thewhole image and it is a good representation, dealing with the automaticallysegmented region provides two things: the feature extraction time decreases,and the query processing phase is accelerated.

Semi-Automatic Texture Feature Extraction: In most of the applications, the users are not interested in the texture of the whole image buta specific region-of-interest. Since the user is provided drawing facilities onthe loaded image, the region-of-interest is determined simply by draggingand dropping the mouse on the image. Similar to the fully automatic case,processing the region-of-interests fastens the system.

Texture Feature Extraction of Whole Image: The texture featureextraction for the whole image is the default case, and is meaningful whenthe whole image is of interest.

OPENCV

OpenCV is released under a BSD license and hence it’s free for both academic and commercial use. It has C++, C, Python and Java interfaces and supports Windows, Linux, Mac OS, iOS and Android. OpenCV was designed for computational efficiency and with a strong focus on real-time applications. Written in optimized C/C++, the library can take advantage of multi-core processing. Enabled with OpenCL, it can take advantage of the hardware acceleration of the underlying heterogeneous compute platform. Adopted all around the world, OpenCV has more than 47 thousand people of user community and estimated number of downloads exceeding 9 million. Usage ranges from interactive art, to mines inspection, stitching maps on the web or through advanced robotics. Infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code.The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce a high resolution image of an entire scene, find similar images from an image database, remove red eyes from images taken using flash, follow eye movements, recognize scenery and establish markers to overlay it with augmented reality, etc. OpenCV has more than 47 thousand people of user community and estimated number of downloads exceeding 7 million. The library is used extensively in companies, research groups and by governmental bodies.

Along with well-established companies like Google, Yahoo, Microsoft, Intel, IBM, Sony, Honda, Toyota that employ the library, there are many startups such as Applied Minds, VideoSurf, and Zeitera, that make extensive use of OpenCV. OpenCV's deployed uses span the range from stitching street view images together, detecting intrusions in surveillance video in Israel, monitoring mine equipment in China, helping robots navigate and pick up objects at Willow Garage, detection of swimming pool drowning accidents in Europe, running interactive art in Spain and New York, checking runways for debris in Turkey, inspecting labels on products in factories around the world on to rapid face detection in Japan.

It has C++, C, Python, Java and MATLAB interfaces and supports Windows, Linux, Android and Mac OS. OpenCV leans mostly towards real-time vision applications and takes advantage of MMX and SSE instructions when available. A full-featured CUDA and OpenCL interfaces are being actively developed right now.

CONCLUSION AND FUTURE SCOPE

This research paper reviewed the main components of a content based image retrieval system, including image feature representation, indexing, query processing, and query-image matching and user's interaction, while highlighting the current state of the art and the key -challenges. It has been acknowledged that it remains much room for potential improvement in the development of content based image retrieval system due to semantic gap between image similarity outcome and user's perception. Since humans classify images according to their objects and concepts, the system must have the ability to recognize object and concept classes in order to automate the process of image annotation. Multiple feature vectors including the texture, shape, contours and color must be used to reduce the semantic gap.

REFERENCES

[1] M. Fakheri, T. Sedghi, M. . G. Shayesteh1 and M. C. Amirani, "Framework for image retrieval using machine learning and statistical similarity matching techniques," *IET Image Process,* pp. 1-11, 2013.

[2] P. MANIPOONCHELVI and K. MUNEESWARAN, "Multi region based image retrieval system," *Indian Academy of Sciences,* pp. 333-344, 2014.

[3] H. J´egou, M. Douze, C. Schmid and P. P´erez, "Aggregating local descriptors into a compact image representation," *IEEE,* pp. 3304-3311, 2010.

[4] Y. Chen, J. . Z. Wang and R. Krovetz, "CLUE: Cluster-Based Retrieval of Images by Unsupervised Learning," *IEEE,* pp. 1187-1201, 2005.

[5] R. Fergus, L. Fei-Fei, P. Perona and A. Zisserman, "Learning Object Categories from Google's Image Search," *IEEE,* 2005.

[6] Y. Chen, X. Li, A. Dick and A. v. d. Hengel, "Boosting Object Retrieval With Group Queries," *IEEE,* pp. 765-768, 2012.

[7] R. Arandjelovi´c and A. Zisserman, "Three things everyone should know to improve object retrieval," *IEEE,* pp. 2911-2918, 2012.

[8] M. Perd'och, Chum and J. Matas, "Content Based Image Retrieval",*IEEE,* pp. 9-16, 2009.

[9] S. . A. Chatzichristofis and Y. S. Boutalis, "CEDD: Color and Edge Directivity Descriptor: A Compact Descriptor for Image Indexing and Retrieval," *Springer-Verlag Berlin Heidelberg,* pp. 313-322, 2008.

[10] Y. Chen and J. Z. Wang, "A Region-Based Fuzzy Feature Matching Approach to Content-Based Image Retrieval," *IEEE,* pp. 1252-1267, 2002.

[11] C.-H. Lin, R.-T. Chen and Y.-K. Chan, "A smart content-based image retrieval system based on color and texture feature," *ELSEVIER,* p. 658–665, 2009.

[12] J. Z. Wang, J. Li and G. Wiederhold, "SIMPLIcity: Semantics-Sensitive Integrated Matching for Picture LIbraries," *IEEE,* pp. 947-963, 2001.

[13] S. Gandhani, R. Bhujade and A. Sinhal, "AN IMPROVED AND EFFICIENT IMPLEMENTATION OF CBIR SYSTEM BASED ON COMBINED FEATURES," *IET,* pp. 353-359.

[14] S. M. H. Khan, A. Hussain and I. F. T. Alshaikhl, "Comparative study on Content-Based Image Retrieval (CBIR)," *IEEE,* pp. 61-66, 2013.

[15] Sreedevi S. and Shinto Sebastian, "Fast Image Retrieval with Feature Levels," *IEEE,* 2013.

[16] S. Ezekiel, Mark G. Alford, David Ferris and Eric Jones,, "Multi-Scale Decomposition Tool for Content Based Image Retrieval," *IEEE,* 2013.

[17] K. Juneja, A. Verma , S. Goel and S. Goel , "A Survey on Recent Image Indexing and Retrieval Techniques for Low-level Feature Extraction in CBIR systems," *IEEE,* pp. 67-72, 2015.